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Increasing the Accuracy of Detection and Recognition in Visual Surveillance

Ali Bazmi*, Karim Faez**
* Department of Electrical, IT and Computer, Islamic Azad University, Qazvin Branch, Qazvin, Iran
** Electrical Engineering Department, Amirkabir University of Technology, Tehran, Iran

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ABSTRACT

Visual surveillance has two major steps of detecting and recognizing moving objects. In the detection stage, moving objects must be detected as quickly and accurately as possible and the influence of environmental light changes and waving trees should be reduced. In this research a block-based method isintroduced in HSV color space in the detection stage. This method did not scan all the pixels of the frame and acted well in situations like sudden light changes. A powerful pattern recognition system should have powerful feature extraction and classification. Note that, feature extraction in gray level or RGB color space has problems such as environmental light changes, adding noise or changes in contrast and sharpness of images, which lead to weak classification. So the HSV color space was used. Here, Block-based Improved Center Symmetric Local Binary Pattern is introduced for feature extraction. In each component of the HSV color space, information of highlight areas in the image such as edge, shape and some texture was extracted. The histogram was calculated in two-level blocks and Support Vector Machine was used for classifying into vehicles, motorcycles and pedestrians. The obtained results in increasing thedetection accuracy and decreasing the spent time were satisfactory.

Corresponding Author:

Ali Bazmi,
Department of Electrical, IT and Computer,
Islamic Azad University, Qazvin Branch,
Qazvin Islamic Azad University, Nokhbegan Blvd, Qazvin, Iran.
Email: ab.bazmi@gmail.com

1. INTRODUCTION

Visual surveillance is one of the major research topics and has two major steps: detection and recognition of moving objects. Detection speed and accuracy are of major importance. In other words, moving objects must be detected as quickly and accurately as possible. Therefore, changes like environmental light and undesired movements like waving trees must have the least impact on the accuracy rate. In this research, a block-based method was used in HSV color space. The examination of powerful pattern recognition systems reveals that, in order to have a powerful pattern recognition system, powerful feature extraction and good classification should exist. In other words, if there is a powerful pattern recognition system, but classification acts weakly or vice versa, the performance of pattern recognition systems is not acceptable. The performance of the system can be guaranteed if both feature extraction and classification act powerfully. It means that feature extraction and classification parts are complementary. Feature extraction system must extract features so that the classification system has the lowest error rate in situations like environmental light changes, noised images or changes in the contrast and sharpness of images.

In this article, a Block-based Improved Centre Symmetric Local Binary Pattern method (B_ICS_LBP) was introduced for feature extraction. This method was used in HSV color space. Also, two-level blocks were used to increase the performance of the system. Using HSV color space had a large impact on the system performance in noised images. Also, Support Vector Machine (SVM) was used for classification.

Three main approaches in the detection and segmentation of moving objects include frame differences, background subtraction and optical flow [1-5]. In frame differences, differences between two consecutive frames are computed and pixels with the intensity higher than a threshold are considered as the moving area. In background subtraction, the moving regions are the image differences between the current image and background image in a pixel to pixel mode, and background image is updated every moment. This approach is strongly sensitive to environmental changes such as changes in light intensity and atmospheric conditions (wind effect on trees). Another method is to use optical flow, which is calculated for each pixel in each frame and is considered for decision [4-7]. This method is more time consuming than the previous ones. All three above-mentioned methods are pixel based.

Adaptive motion histogram method uses histogram of motion flow which has acceptable results in eliminating waving trees but is very time consuming [1]. Background subtraction and temporal analysis method combines temporal image analysis with a reference background image, which results in good detection but not good in eliminating waving trees [2].The most important point about the separation of moving region from dynamic background is to consider the features of moving region and backgroundimage [1]. It should be considered that calculated frames are in RGB color space and should be converted to gray level for processing. Note that, previous methods were sensitive to drastic and sudden changes of light. Also, considering that the impact of changes in the HSV color space is less, the component V was used in HSV color space in this research. Moreover, in dynamic and complex background, there are non-arbitrary movements such as trees. In most vehicle detection methods, they can not be completely removed. The purpose of this paper was to present a new method based on the block in HSV color space. It resulted in increasing the accuracy of desired areas and removing non- desired areas (trees).

In feature extraction, Local Orientation Coding (LOC) is used to extract edge information which depends on edges and acts weakly in images with variation in sharpness [8]. Standard Principal Components Analysis (PCA) is used to extract features, which is sensitive to pose changes and illumination changes [9]. Histogram of Oriented Gradients (HOG) is considered as one of the popular feature extraction methods which is very time consuming and is sensitive in noised images [10-14]. Local Binary Pattern (LBP) is one of the useful methods but it has large computational space [15-19]. SOM & K-means [20] and neural network based method [21] were used in classification part but HOG based method [19] has better results in detection accuracy rate but is time consuming.

2. RESEARCH METHOD

The proposed method had two major steps of detection and classification. In the detection stage, moving objects must be detected as quickly and accurately as possible because speed and accuracy have important roles in visual surveillance systems, and the influence of environmental light changes and waving trees should be reduced. In this research a block-based method was used in HSV color space in the detection stage. This method did not scan all the pixels of the frame and acted well in situations like sudden light changes. The examination of powerful pattern recognition systems, show that in order to have a powerful pattern recognition system, powerful feature extraction and good classification are necessary. So, Block-based Improved Center Symmetric Local Binary Pattern (B_ICS_LBP) was introduced for feature extraction.The features of the images were extracted using the proposed method. In each component of the HSV color space, information of highlight areas in the image such as edge, shape and some texture was extracted, and then the histogram was calculated in two-level blocks and after a good feature extraction, Support Vector Machine was used for classifying into vehicles, motorcycles and pedestrians.

2.1. Moving Object Detection

In this research, a method was proposed for detection and segmentation of moving vehicles in environments with relatively extreme changes in light and with dynamic background. This method obtained better results in comparison with the previous methods. In this research, a block-based method was used for motion detection in which component V of the HSV color space was used.

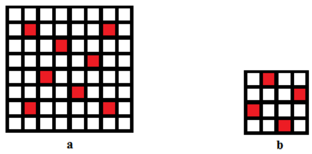
2.1.1. The advantage of using a block-based method

In frames in which there are non-desired areas like trees, a number of methods such as determining size, direction and so on must be used. In addition to being time consuming, the results are not passable. In theblock-based method, the average of non-desired areas has few changes. So, it is the most appropriate measure for eliminating these areas. Meanwhile, due to not scanning the whole image pixels, they act efficiently.

2.1.2. The proposed algorithm for detection

A block-based method was used for detecting moving vehicles which used component V of the HSV color space. Consider F_n as the *nth* frame and b_i as the *ith* block in frame F_n:

1- Split the given frame into blocks of 8×8, each block containing 64 pixels.
2- Extract feature in each 8×8 block, select 8 pixels among 64 pixels according to Fig 1-a and calculate the average of the selected pixels using 1. In fact, 12.5% of pixels are calculated in a block.



a) b)

Figure 1. Selecting pixels a) Selecting 8 pixels of 64 pixels b) Selecting 4 pixels of 16 pixels

3- Classify 8×8 block in comparison with the corresponding block in the previous frame. First, the difference between the results of the features of the corresponding blocks was calculated in frames *n* and *n-1*. The comparison of the result with the threshold resulted in three states as follows: 1-moving area, 2-the combination of moving and non-moving (the suspect) area, 3-non-moving area.

$$mo_{b_i} = \begin{cases} 0 & if\left|m_{b_i} - m_{b_{i-1}}\right| < t1 \\ 1 & if\left|m_{b_i} - m_{b_{i-1}}\right| > t2 \\ x & otherwise \end{cases} \tag{1}$$

where ‘mo’ indicates moving pixels and ‘m’ is the average of selected pixels in block b_i (according to Fig. 1-a). Also ‘t1’ and ‘t2’ are thresholds and ‘x’ indicates the suspect area.

4- Go to the next block if this block becomes moving or non-moving. But, if it becomes the suspect area, 8×8 block should be split into 4 blocks of 4×4.
5- Each 4×4 block contains 16 pixels. First select 4 pixels among 16 pixels of two consecutive frames according to Fig 1.b and then calculate the average of the selected pixels using 1. In fact, 25% of pixels are calculated in a block. The comparison of the result with the threshold resulted in three states as follows:1-moving area, 2-the combination of moving and non-moving (the suspect) area, 3-non-moving area.
6- Go to the next step if this block becomes moving or non-moving. Otherwise, the 4×4 block must be split into 4 blocks of 2×2.
7- In 2×2 block, first, extract the features of the block; so the average of all 4 pixels of the corresponding blocks is calculated in two consecutive frames. Using 2 and the comparison of the result with the threshold, two states are obtained: 1-moving area, 2- non-moving area.

$$mo_{b_i} = \begin{cases} 0 & if\left|m_{b_i} - m_{b_{i-1}}\right| < t1 \\ 1 & if\left|m_{b_i} - m_{b_{i-1}}\right| > t2 \end{cases} \tag{2}$$

2.2. Moving Object Recognition

In the detection stage, all moving areas were detected. Note that, most noises such as waving trees or light changes were eliminated in the proposed detection stage. So, there is not much for elimination. At first, the minimum rectangle of each moving area should be obtained. Then, without considering the size of the area, the feature of the area was extracted by B_ICS_LBP proposed method. And, finally, SVM was used for classification. SVM was used at two stages. First, moving areas were classified into vehicles and non-vehicles, then using the second SVM, non-vehicles were classified into motorcycles and pedestrians.

2.2.1. Obtaining Minimum Rectangle

First, the size of the area was obtained. Considering the size and distance between the camera and the moving area, possible noises remaining from the first stage can be also eliminated. Then, the area was labeled and the minimum rectangle was obtained.

2.2.2. Feature Extraction

The proposed method for feature extraction was B_ICS_LBP, which was used in HSV color space. Standard LBP provided detailed texture information which ranged from 0 to 255 and had large computational space. B_ICS_LBP provided information of highlight areas in the image such as edge, shape and some textures which ranged from 0 to 15 and had less computational space than standard LBP.

LBP is a texture descriptor which provides feature histogram of a texture. The standard version of the LBP acquires the feature of a pixel in the 3×3-neighborhood of each pixel with the value of the central pixel. Let g_c be the central pixel and g_i (i = 0, 1,… ,7) the value of each surrounding pixel at the gray level. If g_i is smaller than g_c, the binary result is set to '0', otherwise, it is '1'. All the results were set to a 8-bit binary value. The calculations are shown in Figs. 2.

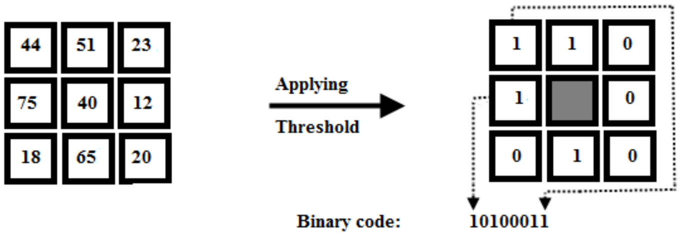


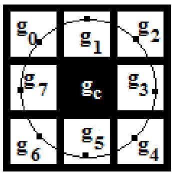
Figure 2. Basic LBP operator

Consider $LBP_{p,r}$ as the feature of a central pixel, where 'p' is the number of neighbors and 'r' is the radius of the circle made by the neighbors. $LBP_{p,r}$ was calculated as follows:

$$LBP_{p,r} = \sum_{i=0}^{P-1} S_1 \ (g_i - g_c) \times 2^i , \qquad S_1 \ (x) = \begin{cases} 1 & if\ x \geq 0 \\ 0 & otherwise \end{cases} \tag{3}$$

2.2.3. The Proposed B_ICS_LBP Method

As mentioned before, standard LBP was at gray level and ranged from 0 to 255 which needed large computational space. B_ICS_LBP ran at two levels. First, Improved Center Symmetric Local Binary Pattern(ICS_LBP) extracted the features; then, the resulted image was divided into blocks at two levels. Instead of comparing each pixel with the central pixel, ICS_LBP compared two symmetric pixels. Let g_c be the central pixel and g_i *(i = 0, 1,… ,7)* the value of each surrounding pixel in each component of HSV color space. According to Fig. 3, there were four pairs of symmetric pixels. First, the difference between the two pairs of pixels was calculated. Then, the result was divided by the maximum of this pair of pixels. The final result was compared with a threshold. If the final result was smaller than the threshold, the binary result was set to '0', otherwise, it was set to '1'. All the results were set to a 4-bit binary value. The result was 4-bit instead of 8-bit and ranged from 0 to 15, instead of 0 to 255, unlike the standard LBP. In contrast, in CS_LBP, only the difference between pairs of symmetric pixels was calculated. Figs. 3 demonstrate the ICS_LBP.



$$ICS\_LBP_{8,1} = \sum_{i=0}^{3} S_2 \left(\frac{|g_i - g_{i+4}|}{Max(g_i, g_{i+4})} \right) \times 2^i$$

$$S_2\ (x) = \begin{cases} 1 & if\ x \geq t \\ 0 & otherwise \end{cases}$$

Figure 3. ICS_LBP operator calculation with p=8 (number of neighbors) and r=1 (radius of the circle)

Consider ICS_LBP$_{p,r}$ as the feature of a central pixelin each component of HSV color space, where 'p'and 'r' are the number of neighbors and the radius of the circle made by the neighbors, respectively. ICS_LBP$_{p,r}$ was calculated as follows:

$$ICS\_LBP_{p,r} = \sum_{i=0}^{\frac{P}{2}-1} S_2\left(\frac{\left|g_i - g_{i+\frac{P}{2}}\right|}{Max\left(g_i, g_{i+\frac{P}{2}}\right)}\right) \times 2^i\ ,\ S_2\ \ (x) = \begin{cases} 1 & if\ x \geq t \\ 0 & otherwise \end{cases} \tag{4}$$

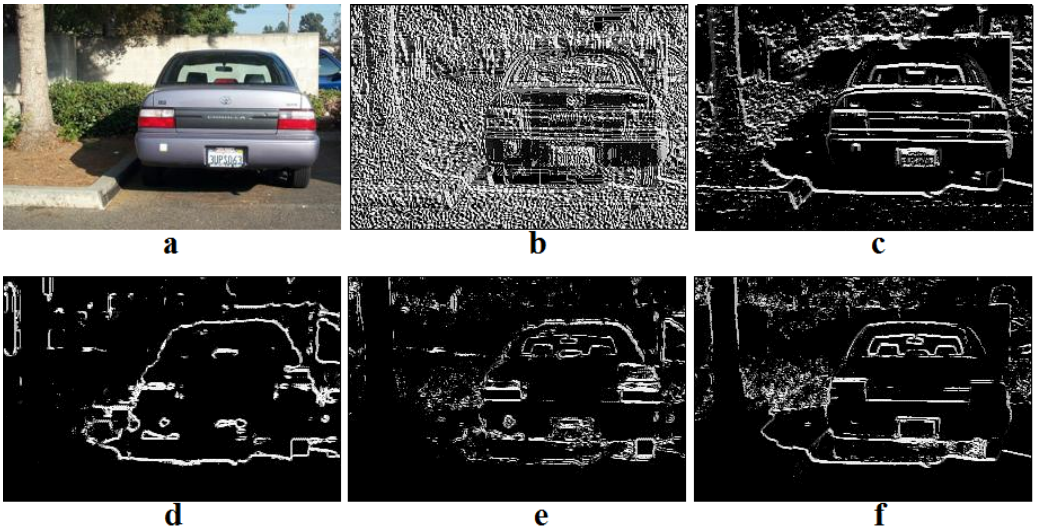


Figure 4. "a" is the original image, "b" is the standard LBP image in gray-level, "c" is the standard CS_LBP image in gray-level, "d", "e" and "f" are proposed ICS_LBP images in H,S and V component of the HSV color space, respectively. Edges in ICS_LBP are more accurate and transparent in comparison with standard LBP and CS_LBP.

According to the characteristics of the image in HSV color space, H, S and V components of HSV color space were used which were *Hue*, *Saturation* and *Value*, respectively. In each component of HSV color space, ICS_LBP was calculated for all pixels. If pixels' values were replaced with ICS_LBP, the result would be ICS_LBP image. Fig. 4-a is the original image, 4-b is the standard LBP image at gray level, 4-c is the standard CS_LBP image at gray level and 4-d,4-e and 4-f are the proposed ICS_LBP image in H,S and V component in HSV color space, respectively. The obtained results showed that the desired edges in ICS_LBP were more accurate and transparent in comparison with standard LBP and CS_LBP.

2.2.4. Extracting Features

First, the ICS_LBP was calculated for all images. As mentioned before, it ranged from 0 to15. In other words, there were 16 binary patterns in each component of HSV color space. Then, the calculated ICS_LBP was divided into blocks in two stages without considering the size of the image. And, the histogram of each block was calculated, which was called B_ICS_LBP. At the first stage of division into blocks, the ICS_LBP image was divided into 2 rows and 2 columns without considering the size of the image (Fig. 5). Therefore, 4 equal blocks were obtained in each component of HSV color space. So, there were 3×4 blocks in the whole HSV color space. At the second stage of division into blocks, the ICS_LBP image was divided into 4 rows and 4 columns (Fig. 5). So, 16 equal blocks were obtained in each component of HSV color space and there were 3×16 blocks in the whole HSV color space. Totally, 60 blocks were obtained and the histogram of each block was calculated. Because the range of histogram was between 0 and 15, there were 16×60 features for each image.

2.2.5. Classification

In order to have a high accuracy rate in pattern recognition systems, both feature extraction and classification systems must work as well as possible. Results should be classified into three classes: vehicles, motorcycles and pedestrians. So, two Support Vector Machines were used for classification. Using the first

SVM, moving areas were classified into vehicles and non-vehicles, then using the second SVM, non-vehicles were classified into motorcycles and pedestrians. In this research, a linear kernel function was used and Sequential Minimal Optimization method (SMO) was used for finding the separating hyper plane.

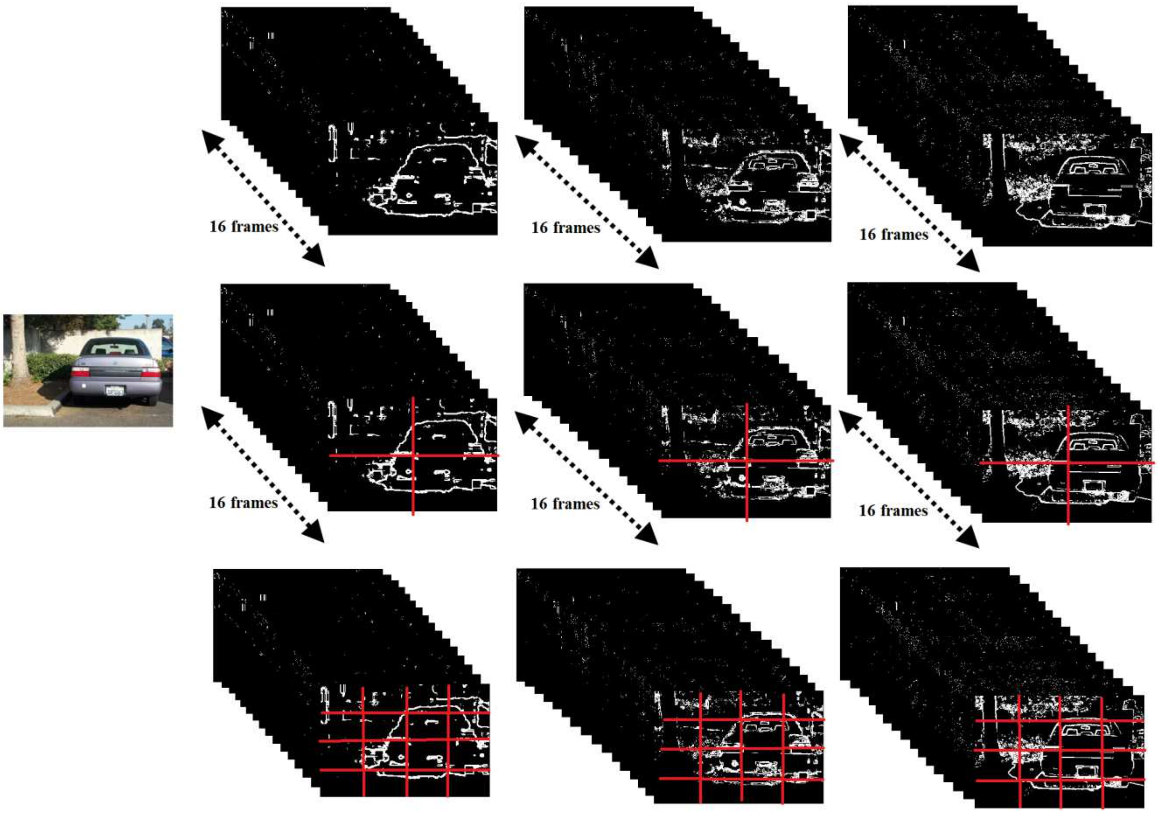


Figure 5. ICS_LBP ranges from 0 to 15. Therefore there will be 16 binary patterns in each component of HSV color space. ICS_LBP is divided into blocks in two stages. At the first stage, ICS_LBP image is divided into 2 rows and 2 columns, and at the second stage, ICS_LBP image is divided into 4 rows and 4 columns. Totally 60 blocks will be obtained and the histogram of each block will be calculated which was called B_ICS_LBP.

3. RESULTS AND ANALYSIS

In the detection stage, the proposed method was compared with the two following methods: adaptive motion histogram [1] and thebackground subtraction and temporal analysis[2]. In the recognition stage, the moving objects were classified into three classes: vehicle, motorcycle and pedestrian and were compared withHOG and SVM based method [20], SOM and K-means method [21], Neural Network based method [22].

3.1. Results of the Detection Stage

In Fig. 6, two blocks were chosen in two consecutive frames and there were changes in these two consecutive frames. The amount of changes in the average of selected pixels of component V in two blocks is shown in Fig. 6. The amount of changes was used for deciding on moving pixels and eliminating the waving trees. Using this method has great impact on detection speed. Because there is no need for extra process on images in order to eliminate waving trees.

In Fig. 7, the result is shown in sudden light changes, which Fig. 7-a is an original frame, Fig. 7-b is the result of background subtraction and temporal analysis method [2] in gray level, and Fig. 7-c shows the result using HSV color space with proposed method. It shows that, using HSV color space, the impact of sudden light changes will be reduced.Moreover, In Fig. 8, the two mentiond methods and the proposed method are evaluated using 5 in which *TP* is the amount of moving pixels that has been correctly detected as vehicles and *TN* is the amount of pixels that must be detected as moving, but has not been detected. In other words, it is the amount of pixels of moving vehicle that has been detected as background. Also, *FP* is the amount of pixels that has been wrongly detected as a moving vehicle. Results of proposed method implies that detected shapes are complete in comparison with both above mentioned methods. Adaptive motion histogram [1] and proposed method has less False Positive (waving trees) but proposed method reduces the execution time in comparison with adaptive motion histogram. Also, in Table 1, the average execution time for each frame and detection accuracy using the proposed method, adaptive motion histogram method [1] and the combination of temporal analysis and background subtraction [2] are given.Also the frames are 240×320 pixels. Executions were done in MATLAB using a computer with the CPU of2 GHz and RAM of 1 G. Due to not scanning the whole image, proposed method reduces the average detection time.

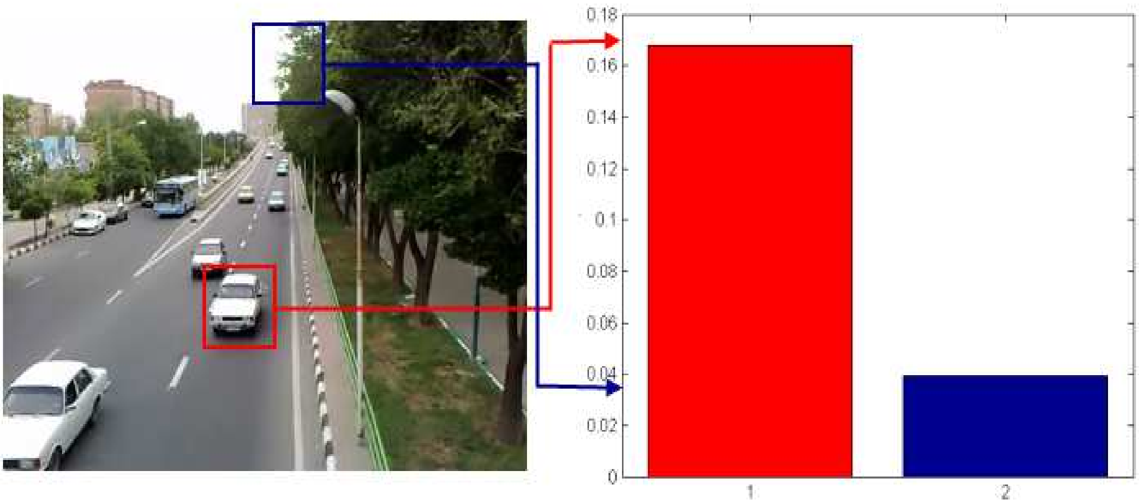


Figure 6.Amount of changes in the average of selected pixels of component V in two blocks of consecutive frames.

a b c

Figure 7. Moving vehicle in sudden light changes, “a” is original image, “b” is moving vehicle without using HSV color space, “c” is moving vehicle with using HSV color space.

$$Result = {}^{TP}/_{(TP + FN + FP)} \quad (5)$$

Table 1. Average time and detection accuracy in detection stage using proposed method, adaptive motion histogram method [1] and Background subtraction and temporal analysis method [2]. Considering that frames are 240×320 pixels. Executions were done in MATLAB using a computer with the CPU of 2 GHz and RAM of 1 G.

Method	Average Time (s)	Accuracy (%)
Proposed method	0.2547	78.4
Adaptive motion histogram	0.6592	69.3
Background subtraction and temporal analysis	0.4014	57.6

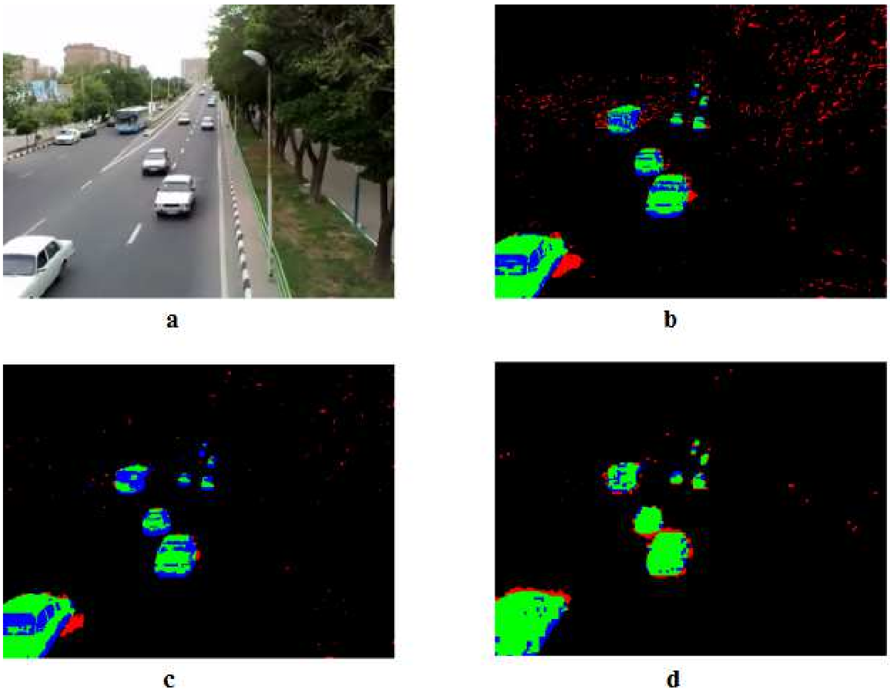


Figure 8. TP,TNandFPare shown in Green, Blue and Red, respectively, “a” is original image, “b” is background subtraction and temporal analysis, “c” is adaptive motion histogram and “d” is proposed method

3.2. Results of the Recognition Stage

As mentioned before, different data sets in different situations were used and the results were classified into three classes: vehicles, motorcycles and pedestrians. Classification accuracy in low quality and noisy data sets in comparison with existing algorithms were satisfactory. Proposed method was compared with HOG and SVM based method [20], SOM and K-means method [21], Neural Network based method [22]. In Fig 9 some classified samples are shown and in Table 2and Fig. 10, the classification accuracy of proposed method in comparison with mentioned methods are shown.

Figure 9. Some classified samples using proposed B_ICS_LBP method

Table 2. Classification accuracy using proposed method, HOG and SVM based method [20], SOM and K-means method [21], Neural Network based method [22], which were classified into: vehicles, motorcycles and pedestrians.

Method	Classification Accuracy (%)		
	Vehicles	Motorcycles	Pedestrians
Proposed method	98.8	96.8	96.4
HOG/SVM based method	97.3	95.9	95.2
SOM & K means	95.8	94.2	93.4
NN based method	95.2	94.0	92.7

Note that the classification accuracy of proposed method and HOG based method are higher than other methods. Andas mentioned before, HOG based methods are time consuming. If these two methods (HOG based method and proposed method) be compared in feature extraction speed, the proposed method acts better than HOG method. Table 3 shows the spent time for these two methods using a same picture with the same size.

Table 3. Average feature extraction time in both HOG based method [20] and the proposed method

Method	Average Time (s)
Proposed method	0.11
HOG/SVM based method	0.23

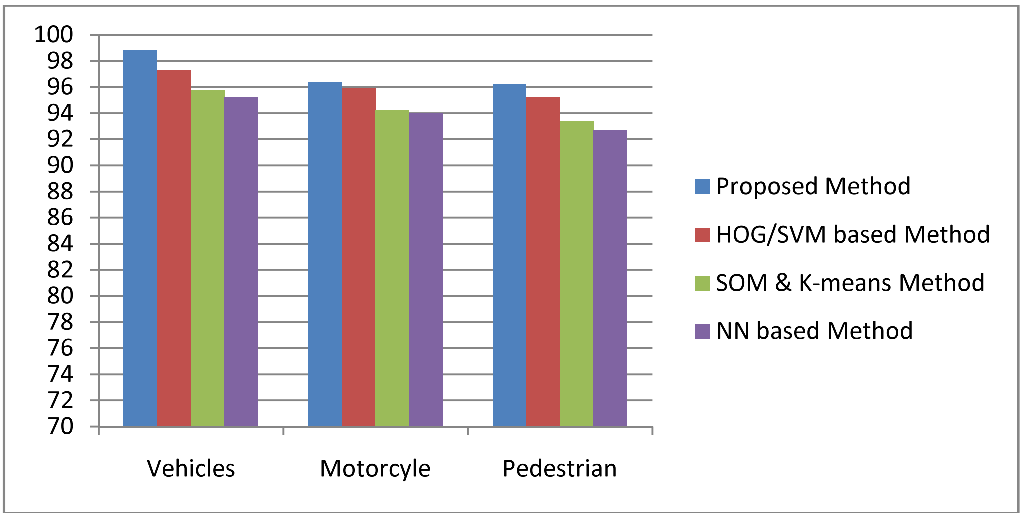


Figure10.Comparing classification accuracy using proposed method, HOG and SVM based method [20], SOM and K-means method [21], Neural Network based method [22].

4. CONCLUSION

Visual surveillance has two major steps: Detection and Recognition of moving objects.In the detection stage, a block-based method was proposed in HSV color space. According to the proposed method, in some cases, instead of evaluating all pixels of a block, the selected pixels were evaluated. Using this method, some advantageswere achieved, like appropriate execution time in comparison with previous methods, increased accuracy of detection and segmentation of moving objects and reduced environment impacts like waving trees and sudden light changes.

In the recognition stage, there were two major steps of feature extraction and classification. If one of them did not work properly, the performance of the whole system would be in trouble. Feature extraction system must extract features so that the classification system has the lowest error rate in situations like environmental light changes, noised images or changes in contrast and sharpness of images. Thus, B_ICS_LBP was introduced for feature extraction which used HSV color space and was less sensitive in the above-mentioned situations. Moreover, SVM was used for classification and the results were compared with the existing algorithms. The results were satisfactory.

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BIOGRAPHY OF AUTHORS

Ali Bazmi received B.S. degree in Software Engineering from Islamic Azad University of Shabestar branch in September 2007 and now is working for M.S. degree in Artificial Intelligence at Islamic Azad University of Qazvin branch. His researches are in Image Processing and Machine Vision, Pattern Recognition, Visual Surveillance.

Karim Faez received his B.S. degree in Electrical Engineering from Tehran Polytechnic University as the first rank in June 1973, and his M.S. and Ph.D. degrees in Computer Science from University of California at Los Angeles (UCLA) in 1977 and 1980, respectively. Prof. Faez was with Iran Telecommunication Research Center (1981-1983) before joining Amirkabir University of Technology in Iran. He was the founder of the Computer Engineering Department of Amirkabir University in 1989 and he has served as the first chairman during April 1989-Sept. 1992. Professor Faez was the chairman of planning committee for Computer Engineering and Computer Science of Ministry of Science, research and Technology (during 1988-1996). His research interests are in Pattern Recognition, Biometric Identification and Recognition, Image Processing, Steganography, Neural Networks, Signal Processing, Farsi Handwritten Recognition, Earthquake Signal Processing, Fault Tolerant System Design, Computer Networks. He is a member of IEEE, IEICE, and ACM.